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Optimism, overconfidence, and insurance decisions

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Abstract

We report experimental evidence regarding overconfidence, optimism, and insurance decisions. Our design distinguishes between an individual's *optimism bias* and *overconfidence bias*, a contribution particularly important for understanding insurance decisions related to risks beyond the purchaser's control. Results show that optimistic participants incur a higher total cost of risk and are more likely to underinsure than non-optimistic participants, even when purchasing insurance maximizes expected payoffs. In contrast, we find that overconfidence does not significantly affect the decision to insure. However, participants with higher overall overconfidence show larger differences in insurance behavior when the risk of loss arises from their own mistakes. © 2021 Academy of Financial Services. All rights reserved.

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1. Introduction

Optimism bias, or the tendency to assign higher subjective probabilities to favorable outcomes, is well documented in the psychology and economics literature. In fact, after decades of controlled studies in psychology, the only individuals identified as consistently free from this bias are the clinically depressed (Pyszczynski, Holt, & Greenberg, 1987). Overconfidence, which can be viewed as a special case of optimism, relates to having a biased perception of one's own skills, prospects, or knowledge. Both optimism and overconfidence theoretically affect decision-making under conditions of risk and uncertainty (De Bondt & Thaler, 1985). Although previous studies differ in how these factors are defined and operationalized, the

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conclusions overwhelmingly suggest that underestimation of the risk of negative outcomes has an economically significant effect on individual and societal well-being.[1] General optimism about events outside of one's own control may cause individuals to underestimate their actual risk, which may lead them to make suboptimal financial decisions. For example, underestimation of expected losses may result in reduced demand for insurance (Kunreuther & Pauly, 2004) and optimism about market performance may affect portfolio allocations (Jacobsen, Lee, Marquering, & Zhang, 2014). Similarly, overestimation of one's financial skills may result in excessive and costly financial market trading (Barber & Odean, 2001) or investment in suboptimal business projects (Malmendier & Tate, 2005).[2] In this article, we focus on the degree to which heterogeneous risk perceptions, which may be affected by both optimism and overconfidence, influence insurance and risk management decisions. To the extent that these biases result in underestimation of personal risks, individuals are hypothesized to have reduced demand for insurance and greater total cost of risk.

Although overconfidence and optimism are widely discussed in the psychology and economics literatures, the influence of these behavioral biases on insurance decision-making has received less attention. Information asymmetry in insurance markets, in which applicants for insurance know more about their own risk characteristics than do insurers, is shown theoretically to create the potential for market failure. With heterogeneous risk types, equilibrium solutions result in separating contracts that encourage individuals to select price and coverage policies that are appropriate to their risk type.[3] For example, a high risk individual might prefer a contract that provides relatively full coverage for a higher premium rate, whereas an individual with a lower risk of loss might select a partial-coverage policy for a lower premium rate. Critical to the success of self-selection equilibria models is that individuals can correctly self-identify their risk type. Bajtelsmit and Thistle (2015) develop a model in which noisy or imperfect information about risk types could result in suboptimal insurance and risk management decisions. In this article, we consider information imperfection caused by individual psychological biases that influence an individual's risk perceptions.

Our study uses a novel experimental design which connects, through large monetary incentives, an earnings task, a frequency estimation task, and insurance decisions. Participants develop subjective estimates of their own and others' performance on an earnings task and decide, in light of their subjective probabilities of loss, whether to fully insure against loss of earnings. In this article, we first focus on the origins of subjective probability estimation, as it depends on task performance, and then develop measures to distinguish between optimism and overconfidence biases in the estimation task. Finally, we investigate how the biases affect the risk management decision to fully insure against loss. Our analysis of insurance decisions in this article continues a stream of research from a large experimental design which, as a whole, considers an extensive set of variables shown theoretically to affect risk management and insurance decisions.[4]

The experiment design allows us to distinguish between an individual's *optimism,* or the general tendency to overestimate favorable outcomes ("wishful thinking"), and their *overconfidence,* the tendency to overestimate their own performance or skills ("I think I'm better than I am") and the relationship between these outlooks.[5] We assess optimism with a treatment manipulation in which a participant's expected payoff is independent of their own performance on a task, but positively related to the performance of others on the same task.

Participants' outlooks range from underconfident to highly overconfident in their own performance and from pessimistic to optimistic about others'. Participants who are optimistic about others' performance are generally confident in their own as well. We find that overconfidence bias does not reduce the likelihood of insurance purchase, but that the highly optimistic are less likely to purchase insurance and, controlling for risk preferences, tend to underinsure.

The remainder of the article is organized as follows. Section 2 describes related literature on insurance and overconfidence. Section 3 explains the experimental design and hypotheses. We provide results in Section 4, and discuss conclusions in the final section.

2. Related literature

The empirical link between overconfidence and the purchase of insurance is an important contribution in support of recent theoretical findings (Huang, Liu, & Tzeng, 2010; Spinnewijn, 2013) and leads to policy implications applicable to insurance contract design and government policy interventions. Huang et al. (2010) show theoretically that hidden overconfidence can lead to insurance market equilibria that are consistent with observed anomalies in insurance markets. They suggest that insurers could use an overconfidence proxy to screen prospective policyholders so as to achieve an advantageous selection equilibrium and that regulators might need to intervene in markets that are operating imperfectly as a result of this type of asymmetric information.[6]

In recent years, researchers have distinguished several different categories of overconfidence bias. However, overconfidence, as a subset of optimism bias, has often remained confounded with a general optimistic outlook. The optimism bias leads individuals to underweight the probability of negative outcomes that are beyond their control, such as an airline crash or a wildfire, and overweight the probability of positive outcomes that are beyond their control, such as winning a lottery. Spinnewijn (2013) refers to this phenomenon as "baseline optimism." For example, Landry and Jahan-Parvar (2011) suggest that failure to purchase flood insurance may be related to residents' reliance on community protection policies (seawalls, beach replenishment, etc.). If the households are overly optimistic regarding the success of the communities' risk management efforts, then they may underinsure against loss.

In addition to a baseline level of optimism, individuals may be overconfident with respect to their influence and/or abilities, which then leads to unrealistic optimism about outcomes, a quality Spinnewijn (2013) terms "control optimism." Royal and Tasoff (2017) show theoretically that overconfident agents are likely to reduce their payoffs by investing too much in capital that complements their ability and too little in capital that substitutes for their own ability. Their experimental results support the theoretical predictions. In the insurance context, this could lead an individual to underinsure if they unrealistically believe they can reduce the frequency or severity of loss through their own actions. A large literature in behavioral economics distinguishes further between different types of control optimism. "Absolute overconfidence" is a term applied to individuals who overestimate their own knowledge, ability, or performance against a given benchmark, such as the prediction that they will perform better on a test or run faster than they actually do (Moore & Healy, 2008). Perhaps the most well-known type of overconfidence is the "better-than-average effect," also termed "over-placement," which refers to overestimation of one's relative performance in a group. An important quality of over-placement is "reference group neglect" in which individuals rank their placement equally high among groups of self-selected members and groups of exogenously assigned members (Camerer & Lovallo, 1999; Moore & Healy, 2008). Other types of control optimism include the "illusion of control," which refers to the case in which individuals erroneously perceive their actions to influence independent events, and "calibration-based overconfidence," or overconfidence in the precision of knowledge.[7] Fellner and Krugel (2012) find evidence that overconfidence assessed with different methods actually reflects separate and distinct biases.

Several recent studies suggest that heterogeneity of risk perceptions (Spinnewijn, 2013) or risk preferences (De Meza & Webb, 2001) can explain the negative correlation between risk and insurance coverage found in some markets.[8] For example, as modeled in Sandroni and Squintani (2007), differences in risk perceptions may lead some high-risk types to believe that they are low-risk types, which can decrease investment in precaution and/or reduce demand for insurance at offered prices. Huang et al. (2010) model optimistic individuals who have subjective loss probabilities that are lower than their objective loss probabilities and "rational" individuals who assess their loss probability correctly. In their model, higher optimism leads to lower likelihood of insurance purchase. Arad (2014) presents a study in which participants are aware of objective probabilities but may assign a higher or lower likelihood due to their own personal motivations that are unrelated to the random event. Arad labels this phenomenon "magical thinking" and notes that beliefs about one's own good or bad luck, regardless of probability distribution can also lead to suboptimal insurance decisions. Honl, Meissner, and Wulf (2017) develop a model in which individual risk-taking behavior depends on cognitive processing of outcomes and probabilities, affect in judgment and decision-making, and upon contextual factors. To the extent that insurance purchasers do not know the objective likelihood of a loss event, it is important to consider biases in estimating risk, and insurance decisions in light of subjective probability estimation.

While our experiment is not motivated as a study of gender effects or risk preferences per se, extant studies suggest that it is important to control for both factors in the analysis. Recent studies designed to investigate gender differences in decision-making find that optimism about conditions or others' performance varies across men and women. In an analysis of survey data that includes several different indicators of optimism, Jacobsen et al. (2014) find men to be more optimistic than women in their expectations about the general economic outlook. In a study spanning three years, Foster and Frijters (2014) find that male university students are more consistently overconfident than females about their future grades. In an experiment task where payoffs depend on team performance, Kuhn and Villeval (2015) find that both men and women expect to outperform others on their team, although women are more optimistic than men about their team members' performance.

Laboratory experiments designed to model insurance decisions offer the opportunity to measure and control for beliefs, risk attitudes, and the set of risk management alternatives. For example, Harrison and Ng (2016) find that, after measuring and controlling for risk preferences, experimental participants tend to make welfare-reducing insurance decisions. In another controlled laboratory experiment, Jaspersen and Aseervatham (2017) find that insurance demand decisions are often driven by biases and the use of heuristics. Laury and McInnes (2003) find that information provided by actuarially fair insurance prices can reduce experimental participants' reliance on heuristics and improve decisions. When experiment participants are allowed to insure against losses that depend on relative performance, Hales and Kachelmeier (2008) show that insurance decisions are affected by biases in performance estimation. For a comprehensive survey on the experimental literature on insurance demand, see Jaspersen (2016) who concludes that the decision context, decision task, and the use of salient incentives all heavily influence experimental results. In this article, we present the results of an experimental study in which we first elicit participants' beliefs about risk perceptions, and then investigate their subsequent decisions in laboratory insurance decision tasks.

3. Experiment procedures and design and hypotheses

In this section, we first describe the design and procedures used in this laboratory experiment, and then explain how this design can be used to test various hypotheses related to the effects of overconfidence and optimism on risk management decisions. The experiment is designed with incentive-compatible earnings and risk management tasks. The design also includes an indirectly incentive-compatible frequency estimation task to elicit subjective probabilities for losses that depend on the participants' own ability and losses that are outside of their influence.[9] The reported subjective probabilities allow us to measure participants' overconfidence in their own performance as well as baseline optimism regarding favorable outcomes. We use these to estimate the impact of overconfidence and optimism biases on incentivized insurance purchase decisions under different risk conditions.

3.1. Procedures overview

Students were recruited from business classes at a large university to participate in a paid experiment. All sessions were conducted with Z-tree (Fischbacher, 2007) in a networked computer lab with partitioned stations. We conducted six sessions, each with ten participants, between June and October 2013. The experiment proceeded through two stages with steps as summarized in Table 1, including participation payment, earnings task, instructions, estimation task, and risk management task.

After participants were paid \$15 up-front in cash (never at risk of loss) and learned the experiment procedures, they earned \$60 for correctly answering at least eight questions on a quiz comprised of twenty questions drawn from previous driver licensing exams for the state in which their university was located.[10,11] For each question, participants were asked to indicate whether they were sure they had answered it correctly. To incentivize participants to carefully make these assessments, the instructions clearly explained the relationship between their quiz performance, others' quiz performance, the probability of loss, and their expected earnings from the experiment. After participants demonstrated their understanding of these

Table 1 Experimental procedures

First stage	
Step 1 Participation payment and procedures overview	• $15 in cash immediately upon entering lab. • Agenda for earnings and risk management tasks.
Step 2 Earnings task	• Twenty multiple choice driving quiz questions distributed on paper. • Monetary incentives to answer correctly. • Indicate whether sure of answer.
Step 3 Instructions	• Risk management task instructions distributed and read aloud. • Relation between earnings, estimation, and risk management tasks explained with examples. • Instructions assessment and review.
Step 4 Estimation task	• Enter driving quiz final answers and whether sure of each. • Enter estimate of own score. • Enter estimate of average score earned by other participants.
Second stage	
Step 1 Risk management tasks	• No Mistakes, Own Mistakes, and Others' Mistakes treatments. • Precaution, insurance, and initial probability of loss treatment manipulations presented in random order.
Step 2 Review all decisions	• Complete all decisions, then review each, one at a time. • Must actively confirm or revise each individual decision.
Step 3 Selection of a treatment for payoff	• Random draw by a participant determines treatment applied for session payment. • Participants are each paid according to their decision in the drawn treatment.

relationships, we proceeded with the estimation task in which they recorded an estimate of the number of questions they had answered correctly and an estimate of the average number correct for the other participants in the session.

In the second stage, participants made risk management and insurance decisions in several treatments. Participants finalized their choices in the program only after experiencing all decisions for the experiment, and no losses or outcomes were realized until after confirmation of all decisions. A random draw at the end of the experiment was used to select the treatment used to determine payoff.

3.2. Treatment design

We use a within-subjects design with 60 participants each completing 8 treatments.[12] This results in 480 participant-treatment observations, some of which are used in the primary analyses, and some of which are used only to check participant rationality or as controls. To minimize order effects, treatment manipulations are randomized across participants in each session.

In each treatment, participants are exposed to a risk of losing $45 from their $60 earnings. Treatment manipulations include the initial loss probability (10% or 32%), and the determinants of overall loss probability. For each initial loss probability, three treatment manipulations that differ in the way that quiz performance determines the overall probability of loss as follows:

- <u>No Mistakes:</u> The risk of loss is implemented as a computer-generated random number—explained with the analogy of a random draw from 100 white and orange ping-pong balls. The risk of loss is expressed as a percentage (10% or 32% orange balls) and also described in terms of number of orange and white balls, respectively. Participants are told that, if an orange ball is drawn, they lose $45.
- <u>Own Mistakes:</u> As in the No Mistakes treatments, there is a draw from a known distribution of orange and white ping-pong balls (10% or 32% orange). Participants are told that they lose $45 if an orange ball is drawn but, if a white ball is drawn, there is a random draw from their own driving quiz questions. If they answered the drawn question correctly, they do not lose any money, but if they answered it incorrectly, they lose $45.
- <u>Others' Mistakes:</u> As in the Own Mistakes treatments, there is a draw from a known distribution of orange and white ping-pong balls (10% or 32% orange). Participants are told that they lose $45 if an orange ball is drawn but, if a white ball is drawn, there is a random draw from a different participant's driving quiz questions. If the other participant answered it incorrectly, they lose $45.

Before learning about whether they experienced a loss, participants made risk management (insurance or precaution) decisions described as the option to pay a dollar cost from their earnings to replace orange balls with white balls. In each case, they were presented with a menu of incremental options as in the example in the Appendix. Consistent with Jasperson and Aseervatham (2015), who emphasize the importance of a choice frame in laboratory experiments of insurance decisions, the insurance and precaution decisions are framed as choice tasks rather than elicitations of willingness to pay for insurance. The cost

Table 2 Probability of losing $45 before risk management decisions in different treatments

Treatments	Initial probability of loss	
	Low (10%)	High (32%)
Own Mistakes: Dependent on own performance	$0.10 + 0.90 * \frac{(20 - Own\,Quiz\,Score)}{20}$	$0.32 + 0.68 * \frac{(20 - Own\,Quiz\,Score)}{20}$
Others' Mistakes: Dependent on others' performance	$0.10 + 0.90 * \frac{(20 - Others'\,Avg.\,Score)}{20}$	$0.32 + 0.68 * \frac{(20 - Others'\,Avg.\,Score)}{20}$
No Mistakes: Independent of performance	0.10	0.32

of insurance is $14.50 and, if purchased in any treatment, it reduces their probability of loss to zero. Each $1.50 spent on precaution reduces the probability of loss by one percentage point in the low probability of loss treatments and by four percentage points in the high probability of loss treatments.[13] In the No Mistakes treatments, participants could reduce their initial probability of loss to zero through buying the maximum level of precaution, making this choice equivalent to full insurance. Buying full precaution is more expensive than insuring in the low probability treatments, but less expensive in the high probability treatments. Our within-participants design allows us to observe that participants who wish to reduce risk to zero make rational choices between precaution and insurance. In the Mistakes treatments where the probability of loss depends on quiz performance, insurance is the only option for reducing risk to zero, because even with the purchase of full precaution (replacing all orange balls with white balls), the risk of loss from mistakes remains.

In the No Mistakes treatments, participants know their risk of loss with certainty whereas, in the Mistakes treatments, they must make subjective assessments over the risk of quiz mistakes to determine their probability of loss. Table 2 summarizes the way in which participants' estimates of quiz scores impact estimates of the probability of loss prior to any investments in risk mitigation.

Table 3 summarizes the optimal insurance decisions for a risk-neutral participant in each of the treatments used in this study.[14] The treatments that do not provide an insurance option are used to categorize and control for participants' risk preferences but are not otherwise included in the primary analysis. The No Mistakes low probability treatment provides a check of participant rationality but is not included in the primary analysis.

Several treatments allow for the possibility of underinsurance by risk-neutral (or risk-averse) participants. In all of the High (32%) Initial Probability of Loss treatments, purchasing insurance is optimal for risk-neutral (or risk-averse) participants in that it results in the highest expected payoff. In the Low (10%) Initial Probability treatments with loss probability independent of performance, the highest expected payoff results from not purchasing any risk mitigation. However, in the treatments where loss probability depends on performance, purchasing insurance is optimal for risk-neutral or risk-averse participants who performed poorly on the quiz. Participants maximize expected payoffs by purchasing insurance if less

Table 3 Optimal risk management decisions to minimize expected loss in each treatment

Treatments	Initial probability of loss	
	Low (10%)	High (32%)
Own Mistakes: Risk depends on own performance	Insure if quiz score < 76% No risk mitigation if > 76%	Insure
Others' Mistakes: Risk depends on others' performance	Insure if quiz score < 76% No risk mitigation if > 76%	Insure
No Mistakes: Risk is independent		
Risk mitigation-precaution and insurance	*No risk mitigation*	Full precaution[a]
Risk mitigation-precaution only[b]	*No risk mitigation*	*Full precaution*

[a] Participants pay to reduce the initial probability of loss before a mistake is drawn in increments of 10 percentage points. In the No Mistakes treatments, the purchase of full precaution reduces the probability of loss to zero and is, therefore, the risk mitigation equivalent to buying insurance in this design. Full precaution is the more efficient means to reduce risk to zero in the high probability treatments, while insurance is the more efficient means in low probability treatments.

[b] Precaution is the only risk management tool. These treatments are used only to categorize and control for risk attitudes.

than 76% of quiz questions are answered correctly. Therefore, overestimation of performance can lead to underinsurance.

3.3. *The incentive for accurate estimation in this experiment design*

In addition to the show-up fee paid at the beginning of Stage 1, participants received a payment at the end of Stage 2 (in private and in cash) based upon their performance, risk management decisions, and chance. Monetary incentives connect the earnings, estimation, and risk management tasks across the two stages. A higher score on the driving quiz decreases the probability of loss in the Own Mistakes treatments in the same way that loss event probability estimation and insurance decisions correspond to expected wealth effects in practice. That is, the estimation task facilitates comparison by the participants between their expected payoff without insurance versus their payoff with insurance. More accurate score estimates improve a participant's ability to make an optimal insurance decision. In summary, higher scores on the quiz reduce the risk of loss in the mistakes treatments, but *overestimation* of scores could lead to suboptimal insurance decisions and lower expected payoffs, and this correspondence rewards participants for accuracy in their estimation.[15] For example, a risk-neutral participant with an initial 10% probability of loss who estimates scoring 90% correct on the driving quiz in the Own Mistakes treatment (expected loss of $8.55) is better off not purchasing insurance for $14.50. However, if the participant's actual performance on the driving quiz is 60% (expected loss of $20.70), the expected payoff is higher *with* insurance. Participants recorded their estimated scores only after they had received all the instructions and passed the instructions assessment, demonstrating they understood how both the probability of mistakes on the quiz and the cost of insurance affected their expected payoffs. At that point, participants were aware of how their quiz scores and score estimation accuracy combined with their risk management and insurance decisions to affect their earnings in the experiment.

As in actual insurance purchase decisions, a participant in the experiment who chooses not to insure based on an optimistic or overconfident estimate of loss probability faces a larger total cost of risk compared with insurance decisions based on more accurate assessments. All responses were completely anonymous. There were no financial or risk management incentives to report higher or lower scores than estimated, and optimal decisions depended on using best estimates. Therefore, participants had incentives to accurately estimate their risk of loss and faced no incentive to inaccurately report their estimates.[16] Consequently, the earnings task is directly incentive-compatible, and the corresponding estimation task is indirectly incentive-compatible, with respect to maximizing final payoffs in the experiment.

Participants completed all decisions before receiving their earnings from the estimation and risk management task. After all decisions were completed, reviewed, and confirmed, a public random draw of a numbered ping-pong ball by a participant determined the treatment used to pay out earnings. Each participant's individual earnings for the chosen treatment depended on a computer-generated random number representing either an orange ball or white ball, and if applicable, random selection of quiz question.

3.4. Hypotheses

In this section, we draw on the existing literature to categorize participants as optimistic or overconfident based on decisions made in the experiment and develop hypotheses about the expected impact of optimism and overconfidence on participants' insurance decisions.

Participants who overestimate their own quiz scores are classified as overconfident in their own knowledge or abilities. We measure a participant's overconfidence as the percentage by which they overestimate (or underestimate) their own score and we call this measure the *gross overconfidence bias*.[17] Gross overconfidence bias ranges from negative (under confident) to positive (overconfident) so that results closer to zero reflect smaller biases.

We measure a participant's general level of optimism (or pessimism) about an unknown probability of loss outside of his or her own control, as the percentage by which they overestimate (or underestimate) the average score of other participants. Our measure of *optimism bias* also ranges from negative (pessimistic) to positive (optimistic), with measures closer to zero reflecting smaller biases. Because an individual may be generally optimistic or pessimistic about outcomes that beyond their control, the accuracy of the participant's estimate of others' average score is used as a proxy for a general tendency to underestimate or overestimate the risk of loss in the experiment, independent of their own knowledge or ability. Participants who overestimate others' scores are classified as optimistic because overestimation of scores corresponds to underestimating the probability of loss due to errors that are beyond their own control.

An optimistic outlook that causes participants to underestimate the chance of loss in general may also influence participants' estimation of their own scores. In other words, a participant's overestimation of their own score may be attributable to overconfidence in their own abilities, a general optimistic outlook, or a combination of the two biases. Therefore, we also measure *net overconfidence bias* as the difference between the errors in estimates of own and others' scores.

Again, there is no compensation associated with relative performance, or reward for above average performance in this experiment. The larger the positive bias in a participant's own estimate compared with the bias in estimating others' average score, the higher that participant's net overconfidence bias. Participants who overestimate their own performance by the same or smaller percentage than they overestimate others' do not exhibit the net overconfidence bias.

Based on the theoretical literature on insurance demand, and the literature on optimism and overconfidence, we develop the following hypotheses to be tested using the experiment design described in the previous section:

Hypothesis 1: Individual biases

A. *Gross Overconfidence Bias:* Participants will exhibit gross overconfidence bias and will, therefore, overestimate their own performance. This measure of bias includes the possibly confounded effects of general optimism and overconfidence in their own ability to minimize the risk of loss.
B. *Optimism Bias:* Participants will exhibit optimism bias and will, therefore, overestimate others' average performance.
C. *Net Overconfidence Bias:* Participants will exhibit net overconfidence bias and will overestimate their own performance to a larger extent than they overestimate others' performance. After adjusting for general optimism about overall performance, participants' estimates of their own performance will reflect a positive bias.

Hypothesis 2: Effect of biases on decision-making

By causing individuals to underestimate the risk of loss, optimism and overconfidence biases will lead to underinsurance against losses. We define underinsurance as declining to insure when the expected payoff is higher with insurance than without it.[18]

A. Gross overconfidence bias will increase the likelihood of underinsurance. Our measure of gross overconfidence bias directly reflects an underestimate of the probability of loss in the Own Mistakes treatments. Therefore, the gross overconfidence bias will be more likely to increase underinsurance against a loss depending on a participant's own performance, than a loss depending on others' mistakes.
B. Optimism bias will increase the likelihood of underinsurance. Errors in assessing risk due to general optimism do not depend on the source of loss. However, our measure of optimism bias directly reflects an underestimate of the probability of loss in the Others' Mistakes treatments. Therefore, the optimism bias will be more likely to increase underinsurance against a loss resulting from others' mistakes than a participant's own mistakes.
C. Net overconfidence bias should not affect the probability of underinsurance in this design because the estimated probability of loss does not depend on relative performance in any way.

Hypothesis 3: Effect of biases on the total cost of risk

In this experiment, participants can spend money on partial risk mitigation and insurance. Participants who do not either insure or purchase precaution face expected losses that depend on their quiz performance, while those who insure incur the known cost of the insurance premium. Therefore, our measure of the total cost of risk is the sum of the expected loss resulting from the risk event and the known amount spent on precaution or insurance. If the overconfident or optimistic choose to pay for precaution rather than fully insuring, they may actually increase their total cost of risk. We hypothesize that:

A. Higher gross overconfidence bias will be associated with greater total cost of risk. The increase in the total cost of risk will be higher when the probability of a loss depends on one's own performance (because the overconfidence bias directly measures errors in assessing risk in the Own Mistakes treatment).
B. Higher optimism bias will be associated with greater total cost of risk. The increase in the total cost of risk will be higher when the probability of loss depends on others' performance (because the optimism bias directly measures errors in assessing risk in the Others' Mistakes treatment).
C. Net overconfidence, the difference between a participant's gross overconfidence and optimism, does not inform the estimation of risk in either Mistakes treatment. Therefore, it will not affect participants' total cost of risk.

The next section presents and discusses the outcomes of participant decisions. Then it introduces controls used in the analysis and presents tests of these hypotheses.

4. Results and analysis

4.1. Summary statistics

Table 4 presents summary statistics for the participants' performance on the earnings and estimation tasks, and summarizes the definitions used for participants' optimism, gross and net overconfidence biases. The summary statistics show that participants overestimate their own performance to a greater extent (9.26%) than they overestimate others' performance (2.10%) and that there is a great deal of within-sample variation in these bias measures.

Given our experiment parameters ($45 loss, $14.50 insurance premium, and precaution alternatives), risk-neutral and risk-averse participants are predicted to purchase insurance (or the full precaution equivalent) for all high initial probability treatments. If they do not purchase insurance, their expected payoff decreases with lower quiz scores in the Mistakes treatments. However, risk-seeking participants in the 32% initial probability No Mistakes treatments may prefer not to purchase insurance in the Mistakes treatments as well. Under the low initial probability of loss, the expected loss is $4.50 in the No Mistakes treatments, and a risk-neutral participant should not purchase insurance. However, in the low initial probability Mistakes treatments, any participant who answers 76% or fewer quiz questions

Table 4 Summary statistics: driving quiz, estimation task, and biases, $N = 60$ participants

	Mean	Minimum	Maximum	Standard deviation
Estimated own quiz score (out of 20)	16.4	11	19	2.06
Percent correct	*82%*	*55%*	*95%*	
Estimated others' quiz score (out of 20)	15.4	10	18	1.94
Percent correct	*77%*	*50%*	*90%*	
Actual quiz score (out of 20)	15.1	12	18	1.50
Percent correct	*75%*	*60%*	*90%*	
$GOC\ bias = \frac{Own\ estimate - own\ score}{Own\ score}$	9.26%***	−18.75%	41.67%	15.80%
$Optimism\ bias = \frac{Estimated\ others'score - others'\ score}{Others'score}$	2.10%	−33.86%	19.46%	12.89%
NOC bias = Overconfidence Bias – Optimism Bias	7.16%***	−23.83%	39.65%	14.72%

***Significantly different from zero at the 99% confidence level, according to the t test and nonparametric signed rank test. GOC and NOC denote gross and net overconfidence, respectively.

correctly has higher expected payoffs from purchasing insurance, making insurance the optimal choice for risk averse and risk neutral participants. As discussed above, overconfidence and/or optimism regarding quiz scores could lead participants to underestimate their risk of loss, which could lead to underinsurance in light of their risk preferences.

While Table 4 shows the average levels of the biases, Table 5 categorizes participants in terms of which biases they exhibit. The table illustrates that participants are relatively unlikely to exhibit one of these biases and not the other. They are more likely to have gross overconfidence and optimism bias or show neither bias. Results in Tables 4 and 5 reveal that while 50% of participants exhibit some degree of optimism, the average level of optimism does not differ significantly from zero. However, 60% of participants exhibit gross overconfidence, and the average level of gross overconfidence is significantly above zero. It follows that their average net overconfidence bias is also significant. In fact, 60% of participants exhibit the net overconfidence bias. In summary, we find descriptive evidence in support of parts A (gross overconfidence bias) and C (net overconfidence bias) of Hypothesis 1, but not part B (optimism bias).

We summarize the insurance and precaution purchase decisions in Table 6. In the No Mistakes treatments, most participants insure against loss, all purchase some form of risk mitigation in the initial 32% probability of loss treatments, and most purchase some risk mitigation in the initial 10% probability of loss treatments. Participants insure against loss more frequently under the Others' Mistakes treatment than the Own Mistakes treatment. Some participants purchase precaution to reduce their risk of loss. For example, in the No Mistakes 32% initial probability treatment, those participants who do not insure, purchase

Table 5 Classification of participants by optimism and gross overconfidence

	Not overconfident	Overconfident (gross overconfidence)
Not optimistic	33%	17%
Optimistic	7%	43%

Differences in proportions are significant at the 99% level in a χ^2 test.

Table 6 Percentages choosing each risk mitigation alternative, by treatment

Mistakes treatment	No Mistakes		Own Mistakes		Others' Mistakes	
Initial probability of loss	32%	10%	32%	10%	32%	10%
Buy insurance or full precaution[a]	65%	43%	57%	55%	68%	67%
Buy partial precaution (average reduction in initial probability)[b]	35% (−20%)	38% (−5%)	43% (−22%)	23% (−5%)	32% (−21%)	17% (−3%)
No risk mitigation	0%	19%	0%	22%	0%	16%

[a] The purchase of full precaution reduces the probability of loss to zero and is, therefore, the equivalent to buying insurance in this design (although not the same cost).

[b] Participants pay to reduce the initial probability of loss before a mistake is drawn in increments of 10 percentage points. The numbers in parentheses show the average percentage point reduction in initial probability. For example, in the No Mistakes 32% initial probability treatment, 35% of participants reduce their probability of loss by an average of 20%.

sufficient precaution to reduce the initial risk from 32% to 12% on average. In the No Mistakes 10% initial probability treatments, participants who buy precaution instead of insurance reduce the risk of loss from 10% to 5% on average.

4.2. Risk attitudes and gender controls

The primary purpose of this research is to analyze the relationship between overconfidence, optimism, and insurance purchase. However, participants make insurance and precaution decisions in light of their estimation of the risk of loss *and* their attitudes about accepting different levels of risk. Previous literature suggests that overconfidence bias (that affects estimation of risk) may vary systematically with gender. At the same time, optimal insurance purchase decisions will differ based on risk attitudes. This subsection discusses summary statistics particular to the risk attitude and gender control variables included in the analysis.

Risk-neutral or risk-averse participants should purchase insurance whenever the expected loss exceeds the insurance premium. All else equal, risk-seeking participants would be less likely to purchase insurance. We use the Precaution Only No Mistakes treatments to provide information about participants' risk attitudes. The within-subject design allows us to observe individual participants' choices across each different treatment. In the Precaution Only No Mistakes treatments, full precaution provides equivalent risk mitigation to insurance. Under an initial probability of loss of 10%, expected payoff is decreasing in precaution, and full precaution (the equivalent of insurance) costs roughly three times the expected loss. Under an initial probability of loss of 32%, expected payoff is increasing in precaution, and the cost of full precaution is only 83% of the expected loss. Therefore, we can identify participants whose behavior is consistent with risk-seeking preferences in the 32% probability of loss treatments, and those who make choices consistent with risk aversion in the 10% probability of loss treatments.

We analyze each participant's choices across No Mistakes Precaution Only treatments to broadly classify risk attitudes. We classify participants as risk averse if they purchase any precaution in the 10% initial probability treatment and also purchase full precaution in the 32% initial probability treatment. Participants who exhibit risk-averse behavior under the 10% initial probability treatment, but risk-seeking behavior under the 32% initial probability treatment are considered to be "reflexive."[19]

We classify participants as risk-seeking if they purchase less than full precaution in the 32% initial probability treatment and also do not purchase any precaution in the 10% initial probability treatment. The risk-seeking classification also controls for an interpretation of optimism in which some participants are optimistic about their "luck" in the outcome of a random draw with a known distribution, even if they are realistic about the distribution itself. Because risk-seekers could optimally choose to remain uninsured in cases where purchasing insurance is optimal for risk-neutral or risk-averse individuals, we control for evidence of risk-seeking behavior in our analysis of the relationship between optimism, overconfidence, and insurance purchase. To avoid multicollinearity problems between this control variable and others, we use the participants' decisions in the Precaution Only No Mistakes treatments

Table 7 Classification of risk attitudes, optimism, and overconfidence

	Percent of participants	Percent of females	Percent of males
Risk seeking	17%	17%	17%
Optimism	50%	50%	50%
Gross Overconfidence	60%	54%	64%
Net overconfidence	67%	63%	69%

(that are not included in the main regressions) only to estimate risk attitudes of the participants.

Table 7 presents the classification of participant risk attitudes, optimism, and overconfidence. Risk-seeking behavior is evident in 17% of the sample. As discussed above, participants who overestimate others' average score are classified as optimistic and Table 4 showed no statistically significant optimism bias in the sample (though this is conservative given the small sample size). However, Table 7 reveals that half of the participants do not overestimate others' scores. (The participants who overestimate others' scores have an average error of 11.74%, while those who underestimate others' scores have an average error of only 7.5%.) We classify participants who overestimate their own score as exhibiting gross overconfidence in their own knowledge or abilities; but some or all of that overconfidence may be due to general optimism. Therefore, we also report the participants classified as exhibiting net overconfidence bias. Comparing these metrics by gender, we find that a larger percentage of men are overconfident, both before and after adjusting for general optimism.

Results in Tables 5, 6, and 7 confirm the presence of optimism and overconfidence. Table 8 summarizes the respective sample correlations of these measures, along with the categorical variables Risk-Seeking and Male. Correlations with the categorical variable Male in Table 8 show that there are no significant gender differences on average in gross overconfidence or optimism biases. However, women's average optimism is slightly higher and gross overconfidence slightly lower than men's. When these effects are combined, the difference-in-differences between men and women is significant for net overconfidence bias. Men exhibit a larger difference between gross overconfidence in their own quiz performance and optimism about others' quiz performance, compared with women. These results are consistent with those reported in Kuhn and Villeval (2015), although the earnings tasks in the two experiments are very different.

Table 8 Biases, risk attitude, and gender correlations

	Gross overconfidence	Optimism	Net overconfidence	Risk seeking	Male
Gross overconfidence	1				
Optimism	0.49***	1			
Net overconfidence	0.65***	−0.35***	1		
Risk seeking	0.08	0.02	0.06	1	
Male	0.19	−0.14	0.33***	0	1

***Significant at the 99% level.

4.3. The effect of overconfidence and optimism on the decision to insure

We now turn our attention to the second set of hypotheses, which considers the effects of the biases on the decision to insure and on the total cost of risk. Because full precaution is equivalent to insurance in the No Mistakes treatments, participants who purchase either of those options in the No Mistakes treatments are counted as buying insurance.

Although some participants purchase partial precaution rather than insurance in the Mistakes treatments, this decision results in their being underinsured when the probability of loss is 32% or higher (unless they are risk-seeking). Participants who are overconfident in their own quiz performance or precaution decisions, or optimistic with respect to others' quiz performance, will underestimate this probability and therefore could make suboptimal insurance decisions in the Mistakes treatments. Hypothesis 2 predicts that the likelihood of underinsurance in the Others' Mistakes treatment will increase with higher levels of optimism bias. It also predicts that insurance decisions in the Own Mistakes treatments will depend on the gross overconfidence bias, which as discussed above, may also include general optimism. We expect both the optimism bias and the gross overconfidence bias to increase the likelihood of underinsurance in the Own Mistakes treatment.

Fig. 1 presents the incidence of underinsurance (from a risk-neutral perspective) for participants in each treatment, according to whether they exhibit optimism (Panel A), gross overconfidence (Panel B), or net overconfidence (Panel C). The optimism bias is associated with underinsurance in the Others' Mistakes low probability treatment, but also in the No Mistakes and Own Mistakes high probability treatments. We find that, as expected, the gross overconfidence bias is associated with underinsurance when payoffs depend on one's own performance, but not others' performance, and the net overconfidence bias has an insignificant impact on underinsurance in this experiment.

We further analyze the effect of the biases on underinsurance through logit regressions presented in Table 9, in which the dependent variable is a dummy variable where Underinsurance =1 indicates underinsurance from a risk-neutral perspective. Categorical independent variables include gender (female is the omitted category), risk treatment type (10% initial probability is the omitted category), and risk-seeking attitude (no evidence of risk seeking is the omitted category).[20] Regression coefficients are presented in terms of log odds. Due to the strong relationship between the biases, we run separate regression models, including different bias measures as independent variables in each.

The top panel of Table 9 presents analysis of the Mistakes treatments (N = 240 decisions, with 60 standard error clusters). Conceptually, we would expect optimism and gross overconfidence (that encompasses optimism) to influence insurance decisions in both Mistakes treatments. At the same time, our measure of optimism directly informs subjective probability of loss in the Others' Mistakes treatment and our measure of gross overconfidence directly informs subjective probability of loss in the Own Mistakes treatment. Therefore, we are especially interested in the significance of interaction terms for the biases and Mistakes treatment. In particular, we would expect the gross overconfidence measure to have a more significant impact on underinsurance in the Own Mistakes treatments and general optimism to be more influential in the Others' Mistakes treatments.

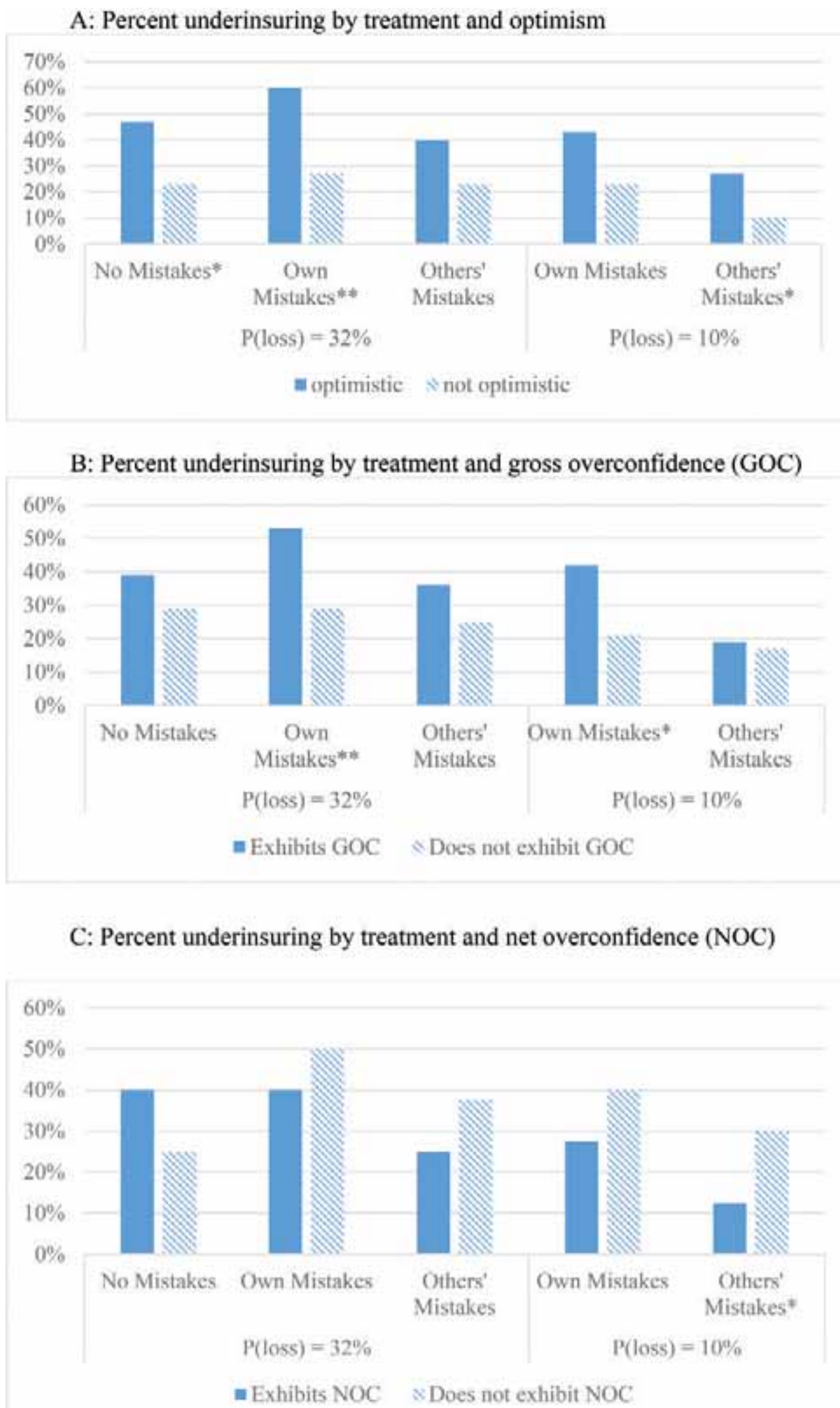

Fig. 1. Panel A: Percent underinsuring by treatment and optimism. Panel B: Percent underinsuring by treatment and gross overconfidence (GOC). Panel C: Percent underinsuring by treatment and net overconfidence (NOC) *Notes:* Differences in proportions are significant at the 90% level (*) based on a χ^2 test. P(loss) represents the initial probability 32% and 10% treatments; No Mistakes, Own Mistakes, and Others' Mistakes denote No Mistakes, Own Mistakes and Others' Mistakes treatments, respectively.

Table 9 Determinants of underinsurance, logit regression coefficient estimates and (standard errors)

	Mistakes treatments, N =240, standard errors clustered by participant					
	Model 1: Gross overconfidence		Model 2: Optimism		Model 3: Net overconfidence	
	Main effects	Interaction effects	Main effects	Interaction effects	Main effects	Interaction effects
Intercept	−1.5050*** (0.3972)	−1.6089*** (0.4104)	−1.7894*** (0.4095)	−1.8065*** (0.4121)	−1.4986*** (0.4248)	−1.5706*** (0.4357)
Others' Mistakes	−0.7122*** (0.2393)	−0.4965* (0.2507)	−0.7607*** (0.2532)	−0.7202*** (0.2369)	−0.7332*** (0.2419)	−0.6055** (0.2600)
GOC bias	0.7388 (1.5140)	1.7013 (1.6054)				
GOC × Others' Mistakes		−2.1804* (1.2481)				
Optimism bias			5.0281*** (1.5427)	5.4407*** (1.6508)		
Optimism × Others' Mistakes				−0.9332 (1.7860)		
NOC bias					−3.1288* (1.7988)	−2.1298 (1.7532)
NOC × Others' Mistakes						−2.4306 (1.5311)
Male	0.5600 (0.4644)	0.5647 (0.4672)	0.8271* (0.4439)	0.8287* (0.4460)	0.9287* (0.4915)	0.9361* (0.4924)
Initial probability = 32%	0.6243* (0.2716)	0.6285** (0.2743)	0.6669** (0.2908)	0.6677** (0.2919)	0.6428** (0.4915)	0.6449** (0.2849)
Risk-seeking	1.6746*** (0.3876)	1.6890*** (0.3977)	1.8039*** (0.4439)	1.8057*** (0.3682)	1.8305*** (1.7988)	1.8599*** (0.3959)

	No Mistakes p(loss) = 32% treatment, N = 60		
	Model 1: Gross overconfidence	Model 2: Optimism	Model 3: Net overconfidence
Intercept	−1.1615 (0.5205)	−1.2197** (0.4953)	−1.0912** (0.4818)
GOC bias	1.0152 (1.8618)		
Optimism bias		2.4298 (2.3574)	
NOC bias			−0.7252 (0.6037)
Male	0.7046 (0.5946)	0.8563 (0.6015)	0.8338 (0.6037)

Notes: *, **, *** designate significance at the 90%, 95%, and 99% confidence intervals, respectively. The dependent variable is zero if the participant did not underinsure, and 1 if they did. Coefficients are presented in log odds terms. GOC and NOC denote gross and net overconfidence, respectively.

Controlling for the biases, initial probability of loss, and risk-seeking preferences, we find that participants are significantly less likely to underinsure in the Others' Mistakes treatments than in the Own Mistakes treatments. Model 1 shows that gross overconfidence itself is not a significant predictor of underinsurance. However, the interaction effect in the second column reveals that the difference in the probability of underinsuring between the Own and Others' Mistakes treatment does depend on gross overconfidence. As gross overconfidence increases, there is a greater increase in the likelihood of underinsuring in the Own Mistakes compared with the Others' Mistakes treatments. In other words, participants with higher gross overconfidence are even more likely (compared with those who are less overconfident) to make suboptimal insurance decisions when the risk of loss depends on their own performance than when it depends on others' performance. This is somewhat consistent with the Hypothesis 2 predictions about biases.

In Model 2, we find that participants who exhibit higher levels of optimism bias are significantly more likely to underinsure. However, the interaction between Optimism and the Others' Mistakes treatment is not significant, which suggests that the effect of optimism is no more influential in the Others' Mistakes treatment than in the Own Mistakes treatment. Finally, In Model 3, we find that net overconfidence bias has a negative relationship with underinsurance that is weakly significant and independent of the Mistakes treatment. We attribute this result to the fact that net overconfidence is decreasing in optimism, which as discussed above, has a strong positive and significant relationship with the probability of underinsuring across both Mistakes treatments.

The second panel of Table 9 displays results for the No Mistakes condition. In this treatment, participants can only underinsure in the 32% initial probability of loss treatment, because purchasing no risk mitigation is the payoff-maximizing choice in the 10% initial probability treatment. Therefore, we examine underinsurance decisions separately for the No Mistakes, 32% probability of loss treatment ($N = 60$), and find that, as expected, none of the biases have a significant effect.[21] This suggests that participants' bias stems from their beliefs about the probability of loss rather than optimism or pessimism about luck when confronting a known distribution. However, the insignificant effect on the insurance decision may also be attributable to the smaller sample size using only one treatment for this statistical test.

4.4. The effect of overconfidence and optimism on the total cost of risk

As described in Hypothesis 3, the relationship between the total cost of risk (the sum of the expected loss resulting from the risk event and the known amount spent on precaution or insurance) and the biases provides a way to examine the cost of underinsurance, in particular when participants have access to alternative risk mitigation measures instead of insuring. For example, given the experiment parameters in the 10% initial loss probability Own Mistakes treatments, a participant who answers 70% of the quiz questions correctly and insures faces a total cost of \$14.50 (out of their \$60 earnings). If they underinsure by neither purchasing insurance nor precaution, they face an expected loss of \$16.70 in the initial 10% probability treatment. However, if that participant pays for precaution to reduce the initial probability of loss to 5%, then the total cost of risk, including the cost of precaution, is actually even higher at $22.60. Participants who are overconfident about the effects of precaution increase their total cost of risk when they choose to purchase partial precaution instead of either insuring or doing nothing.

Table 10 presents results of a generalized least squares regression estimating the impact of the biases and control variables on the total cost of risk. As in the previous regressions, we separately analyze the effects of the three types of biases. The results for Model 1 show that gross overconfidence bias is a statistically and economically significant factor increasing the cost of loss in the Own Mistakes treatment. Furthermore, the effect is significantly lower for participants in the Others' Mistakes treatments as compared with the Own Mistakes treatments. Overconfidence in one's own ability is more costly when the expected loss depends on own performance.

In Model 2, we find that optimism bias also increases the total cost of risk, but there is no significant difference in this relationship across mistakes treatments. This too is expected, since errors in assessing risk due to general optimism do not depend on the source of loss. Finally, Model 3 confirms that net overconfidence bias does not significantly increase the total cost of risk. However, as the combined results for gross overconfidence and optimism imply, the impact of net overconfidence on the total cost of risk is lower in the Others' Mistakes treatment than in the Own Mistakes treatment. As in the previous table, the smaller sample size when using only the data from the No Mistakes treatment ($N = 60$) reduces the power of the test but, in this case, we still find the effect of net overconfidence to be marginally significant.

5. Conclusions

This article contributes to the literature by providing experimental evidence regarding the effects of overconfidence and optimism on insurance decisions. In the existing literature, optimism is sometimes confounded with overconfidence, and we contribute an innovative design that distinguishes between overconfidence regarding the likelihood of a favorable outcome resulting from one's own performance versus optimism regarding the likelihood of a favorable outcome outside of one's own influence. We find that these psychological biases have important implications for insurance in that they can cause individuals to underestimate their risk and, therefore, underinsure, resulting in a higher total cost of risk. This effect is stronger for insurance over risks that depend on one's own performance as compared with exogenous risks. Our results contribute to the growing body of literature on the effect of psychological biases on financial decisions and reinforce the importance of careful measurement of overconfidence bias in laboratory experiments. This distinction is particularly important for understanding insurance decisions related to risks outside of the purchaser's control. The relationship between overconfidence and optimism may also help explain the perceived tradeoffs between risk mitigation and insurance decisions.

Our results show that, after controlling for risk-seeking behavior, participants are more likely to make suboptimal insurance decisions when the risk of loss depends on their own

Table 10 Determinants of total cost of risk, generalized least squares regression coefficient estimates and (standard errors)

	Determinants of underinsurance in Mistakes treatments, N =240, standard errors clustered by participant					
	Model 1: Gross overconfidence		Model 2: Optimism		Model 3: Net overconfidence	
	Main effects	Interaction effects	Main effects	Interaction effects	Main effects	Interaction effects
Intercept	14.6311 (0.3988)	14.8373*** (0.4034)	14.5583*** (0.3931)	14.5297*** (0.3922)	14.8056*** (0.4373)	14.6504*** (0.4340)
Others' Mistakes	−0.4847 (0.3302)	0.0320 (0.2900)	−0.4847 (0.3302)	−0.4275 (0.3102)	−0.4847 (0.3302)	−0.1743 (2.6154)
GOC bias	3.2637 (2.0064)	6.0541*** (2.7703)				
GOC × Others' Mistakes		−5.5808*** (0.4352)				
Optimism bias			5.6885*** (1.6254)	7.0494*** (1.9744)		
Optimism × Others' Mistakes				−2.7218 (1.9373)		
NOC bias					−0.4847 (0.3302)	1.4179 (0.5898)
NOC × Others' Mistakes						−4.3369* (2.3555)
Male	0.4099 (0.5369)	0.4099 (0.5381)	0.8170 (0.5159)	0.8170 (0.5170)	0.6780 (0.5401)	0.6780 (0.5413)
Initial probability = 32%	2.1959*** (0.4306)	2.1959*** (0.4315)	1.8272*** (0.4937)	2.1959*** (0.4315)	2.1959 (0.4306)	2.1959*** (0.4315)
Risk-seeking	1.7596*** (0.5186)	1.7596*** (0.5381)		1.8272*** (0.4947)	1.8831*** (0.5408)	1.8831*** (0.5419)

	Determinants of total cost of risk in No Mistakes p(loss) = 32% treatment, N = 60		
	Model 1: Gross overconfidence	Model 2: Optimism	Model 3: Net overconfidence
Intercept	12.5650*** (0.2367)	12.6446*** (0.2222)	12.58*** (0.2194)
GOC bias	0.6910 (0.8133)		
Optimism bias		−1.0439 (1.0396)	
NOC bias			1.7385* (0.9780)
Male	0.0212 (0.9299)	0.0236 (0.2568)	−0.1062 (0.2588)

Notes: *, **, ***designate significance at the 90%, 95%, and 99% confidence intervals, respectively. GOC and NOC denote gross and net overconfidence, respectively.

performance than others' performance. Optimistic participants are more likely to underinsure than non-optimistic participants. Overconfidence does not have a significant effect on the decision to purchase insurance, although participants with higher overall overconfidence show larger differences in behavior when they are responsible for the risk of loss than when it is beyond their control.

Analysis of the total cost of risk, including both the expected loss and the cost of precaution or insurance, under different treatments provides similar evidence about the influence of these psychological biases. Overconfidence and optimism both significantly increase the total cost of risk. However, overconfidence has a significantly lower effect on total cost when the loss event is triggered by someone else's error. Optimism bias increases the cost by about the same amount regardless of whether the risk depends on one's own actions. These results suggest that general optimism extends to outcomes that depend on one's own ability, but overconfidence in one's own performance does not affect the decision to mitigate risks due to factors outside of one's own control, such as those resulting from nature or from others' errors.

The laboratory evidence reported in this article offers a potential explanation for the underinsurance against catastrophe that has been observed in the market. Beliefs, together with risk tolerance, preferences, or general probability misperceptions may provide alternative explanations for some of the observed insurance decision puzzles. For example, Jacobsen et al. (2015), who study asset allocation decisions under uncertainty, find that optimism about outcomes and optimism about the level of risk are as important as risk aversion in explaining asset allocation. Spinnewijn (2013) notes that, while heterogeneity in beliefs informs insurance policy design, it is very difficult to obtain direct evidence about beliefs. Laboratory results such as ours provide a first step in connecting beliefs to insurance decisions, with more control than surveys or behavioral proxies for perceptions. While convenience samples of students provide for a strong degree of laboratory control, it would interesting to further explore these issues with a more diverse participant population. Future research should also consider in greater detail the influence of these biases on individual perceptions about the effectiveness of different risk mitigation alternatives.

Notes

1 Theoretical explanations in economics and evolutionary biology have also illustrated conditions under which optimism or overconfidence bias can be individually welfare-improving (compared to rational expectations), a second best solution in the presence of other biases, and even a necessary adaptation for species survival. See, for instance Brunnermeier and Parker (2005), Besharov (2004), and Johnson and Fowler (2011).

2 This definition of overconfidence assumes misperceptions rather than a well-calibrated assessment of one's own relative abilities. Well-calibrated confidence does not produce lower results. For example, Fielder (2011) finds that virtual traders who self-report as better than average, in fact earn above average virtual profits.

3 The adverse selection literature in insurance originated with the seminal work of Rothschild and Stiglitz (1976). See Dionne, Fombaron, and Doherty (2013) for a more complete summary of this extensive literature.

4 In Bajtelsmit, Coats, and Thistle (2015), the authors focus on the other considerations addressed by the experiment design, including the effect of ambiguity on risk management decisions and the tradeoff between taking precaution and purchasing insurance, as well as replicability of other researchers' results.

5 We acknowledge that there is a great deal of inconsistency in terminology and trait measurement across the overconfidence literature, both theoretical and empirical. See Clark and Friesen (2009) and Spinnewijn (2013) for more complete reviews of this literature.

6 De Meza and Webb (2001) show that insurers can design contracts that will result in an equilibrium which they term "advantageous selection" in which the risk-averse agent buys insurance and also invests in some precaution. The risk-neutral agent does not take precaution or buy insurance.

7 However, recent research suggests that calibration-based overconfidence observed in confidence interval reporting may be overstated because of the measurement instrument (Blavatskky, 2009; Cesarini, Sandewall, & Johannesson, 2006; Glaser, Langer, & Weber, 2013; Soll & Klayman, 2004).

8 See Chiappori and Salanie (2013) for a review of this literature.

9 Experiments by Cesarini et al (2006), Blavatskyy (2009), and Clark and Friesen (2009) suggest that frequency estimation tasks provide better measures of overconfidence relative to confidence interval estimation tasks because of the improvement in incentive-compatibility, better alignment of accuracy and information, and because framing a forecast as a frequency is a much more natural cognitive task.

10 The earnings, probability estimation, and risk management tasks were explained in a Power Point presentation at the front of the room, with the instructions read aloud. Participants took an instructions assessment to confirm they understood how their earnings would be determined and were able to ask questions.

11 Participants were required to have a valid state driver's license as a condition of participation in the experiment. The driving quiz was designed to include a sufficient number of easy questions such that all participants were expected to be able to achieve the minimum score, but also some more difficult questions to minimize the number who could achieve a perfect 20 out of 20 correct.

12 The within-participants design provides for much greater statistical power than a between-participants design of the same size (see Bellamare, Bissonnette, and Kroger, 2014 and Charness, Gneezy, and Kuhn, 2012). We obtain more participant observations and cluster standard errors at the participant level in our analysis.

13 The return to taking precaution is higher for the high-risk treatments than the low-risk treatments due to the assumption of greater productivity of precaution

under high initial risk. For a theoretical justification, see Bajtelsmit and Thistle (2015).

14 The full design also included four additional treatments, in which the probability of loss depended on own and others' performance under high and low initial probabilities of loss. However, in those treatments, participants could neither reduce loss probability to zero, nor insure against loss and, therefore, we do not include or analyze them in this article. See Bajtelsmit et al. (2015).

15 Although there are other methods of incentivizing participants, such as scoring rules that reward estimates but penalize errors, participant risk preferences have been shown to affect their choices. See, for example, Andersen, Fountain, Harrison, and Rutström (2014) and Harrison, Martinex-Correa and Swarthout, (2014). Other probability elicitation mechanisms depend on independence between agents' actions and the probability of the risky event (Armentier and Treich, 2013) and on the agent having no stake in the risky event (Karni, 2009).

16 *Estimating* one score to use in risk management decision making, but *recording* a different score, while technically possible, would be inconsistent with payoff maximization efforts because it would increase the cognitive difficulty of the risk management task and potentially increase the chance of making a costly risk management error and, therefore, would not be incentive compatible with maximizing experiment payoffs.

17 We thank an anonymous referee for suggesting the "gross overconfidence" and "net overconfidence" labels.

18 Because this definition only applies to risk-averse and risk-neutral participants, we control for risk-seeking behavior in our analysis.

19 This classification is discussed in detail in an earlier article by the authors where the No Mistakes treatments is compared to the alternative to buy insurance against the No Mistakes Precaution Only treatments and show that (1) participants purchase the more efficient means of risk mitigation, and (2) that participants are consistent in their risk mitigation decisions across treatments. Comparison of the Precaution Only Mistakes treatments to the Precaution Only No Mistakes treatments shows that participants respond predictably to the lower effectiveness of precaution by purchasing less precaution in the Mistakes treatments.

20 Identified through behavior in the Precaution Only No Mistakes treatments.

21 The risk-seeking dummy variable is not included because, in the treatments used to determine risk attitudes (Precaution Only No Mistakes), a risk-seeking identification is indistinguishable from underinsurance in the high probability of loss insurance treatments.

Appendix: Examples of choices available in high and low initial probability treatments

Initial high probability of loss example: Choose one of the following options below.

Decision	Up-front cost to replace orange balls	New number of orange balls	New number of white balls	Probability orange ball is drawn
A	$0	32	68	32%
B	$1.50	28	72	28%
C	$3.00	24	76	24%
D	$4.50	20	80	20%
E	$6.00	16	84	16%
F	$7.50	12	88	12%
G	$9.00	8	92	8%
H	$10.50	4	96	4%
I	$12.00	0	100	0
J (Insurance)	$14.50	32	68	N/A

Your decision in Scenario 2: ____________________

Initial low probability of loss example: Choose one of the following options below.

Decision	Up-front cost to replace orange balls	New number of orange balls	New number of white balls	Probability an orange ball is drawn
A	$0	10	90	10%
B	$1.50	9	91	9%
C	$3.00	8	92	8%
D	$4.50	7	93	7%
E	$6.00	6	94	6%
F	$7.50	5	95	5%
G	$9.00	4	96	5%
H	$10.50	3	97	3%
I	$12.00	2	98	2%
J	$13.50	1	99	1%
K	$15.00	0	100	0
L (Insurance)	$14.50	10	90	N/A

Your decision in Scenario 8: ____________________

References

Andersen, S., Fountain, J., Harrison, G. W., & Rutström, E. E. (2014). Estimating subjective probabilities. *Journal of Risk and Uncertainty*, *48*, 207–229.

Arad, A. (2014). Avoiding greedy behavior in situations of uncertainty: The role of magical thinking. *Journal of Behavioral and Experimental Economics*, *53*, 17–23.

Armentier, O., & Treich, N. (2013). Eliciting beliefs: Proper scoring rules, incentives, stakes, and hedging. *European Economic Review*, *62*, 17–40.

Bajtelsmit, V., Coats, J., & Thistle, P. (2015). The effect of risk ambiguity on risk management choices: An experimental study. *Journal of Risk and Uncertainty*, *50*, 249–280.

Bajtelsmit, V., & Thistle, P. (2015). Liability, insurance and the incentive to obtain information about risk. *The Geneva Risk and Insurance Review*, *40*, 171–193.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, *116*, 261–292.

Bellemare, C., Bissonnette, L., & Kroger, S. (2014). *Statistical Power of Within and Between-Subjects Designs in Economic Experiments.* Discussion Paper No. 8583. Germany: Institute for the Study of Labor.

Besharov, G. (2004). Second-best considerations in correcting cognitive biases. *Southern Economic Journal*, *71*, 12–20.

Blavatskyy, P. R. (2009). Betting on own knowledge: Experimental test of overconfidence. *Journal of Risk and Uncertainty*, *38*, 39–49.

Brunnermeier, M., & Parker, J. (2005). Optimal expectations. *American Economic Review*, *95*, 1092–1118.

Camerer, C. F., & Lovallo, D. (1999). Overconfidence and excess entry: an experimental approach. *American Economic Review*, *89*, 306–318.

Cesarini, D., Sandewall, O., & Johannesson, M. (2006). Confidence interval estimation tasks and the economics of overconfidence. *Journal of Economic Behavior & Organization*, *61*, 453–470 .

Charness, G., Gneezy, U., & Kuhn, M. (2012). Experimental Methods: Between-subject and Within-subject Design. *Journal of Economic Behavior and Organization*, *91*, 1–8.

Chiappori, P., & Salanie, B. (2013).Asymmetric information in insurance markets: Predictions and Tests. In G. Dionne (Ed.), *Handbook of Insurance* (pp. 397–422). New York, NY: Springer.

Clark, J., & Friesen, L. (2009). Overconfidence in forecasts of own performance: An experimental study. *The Economic Journal*, *119*, 229–251.

De Bondt, F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*, 793–805.

De Meza, D., & Webb, D. C. (2001). Advantageous selection in insurance markets. *The Rand Journal of Economics*, *32*, 249–262.

Dionne, G., Fombaron, N., & Doherty, N. (2013).Adverse selection in insurance contracting. In G. Dionne (Ed.), *Handbook of Insurance* (pp. 231–280). New York, NY: Springer

Fellner, G., & Krugel, S. (2012). Judgmental overconfidence: Three measures, one bias? *Journal of Economic Psychology*, *33*, 142–154.

Fiedler, M. (2011). Experience and confidence in an internet based asset market experiment. *Southern Economic Journal*, *78*, 30–52.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for readymade economic experiments. *Experimental Economics*, *10*, 171–178.

Foster, G., & Frijters, P. (2014). The formation of expectations: competing theories and new evidence. *Journal of Behavioral and Experimental Economics*, *53*, 66–81.

Glaser, M., Langer, T., & Weber, M. (2013). True overconfidence in interval estimates: Evidence based on a new measure of miscalibration. *Journal of Behavioral Decision Making*, *2*, 405–417.

Hales, J., & Kachelmeier, S. (2008). Predicting relative performance in economic competition. *Journal of Behavioral Finance*, *9*, 187–192.

Harrison, G., Martinez-Correa, J., & Swarthout, T. (2014). Eliciting subjective probabilities with binary lotteries. *Journal of Economic Behavior & Organization*, *101*, 128–140.

Harrison, G., & Ng, J. (2016). Evaluating the expected welfare gain from insurance. *Journal of Risk and Insurance*, *83*, 91–120.

Honl, H., Meissner, P., & Wulf, T. (2017). Risk attribution theory: An exploratory conceptualization of individual choice under uncertainty. *The Journal of Behavioral and Experimental Economics*, *67*, 20–27.

Huang, R., Liu, Y., & Tzeng, L. (2010). Hidden overconfidence and advantageous selection. *The Geneva Risk and Insurance Review*, *35*, 93–107.

Jacobsen, B., Lee, J., Marquering, W., & Zhang, C. (2014). Gender differences in optimism and asset allocation. *Journal of Economic Behavior & Organization*, *107*, 630–651 .

Jaspersen, J. (2016). Hypothetical surveys and experimental studies of insurance demand: A review. *Journal of Risk and Insurance*, *83*, 217–255.

Jaspersen, J., & Aseervatham, V. (2017). The influence of affect on heuristic thinking in insurance demand. *Journal of Risk and Insurance*, *84*, 239–266.

Johnson, D., & Fowler, J. (2011). The evolution of overconfidence. *Nature*, *477*, 317–320.

Karni, E. (2009). A mechanism for eliciting probabilities. *Econometrica*, *77*, 603–606.

Kuhn, P., & Villeval, M. (2015). Are women more attracted to co-operation than men? *The Economic Journal*, *125*, 115–140.

Kunreuther, H., & Pauly, M. (2004). Neglecting disaster: Why don't people insure against large losses? *Journal of Risk and Uncertainty*, *28*, 5–21.

Landry, C., & Jahan-Parvar, M. (2011). Flood insurance coverage in the coastal zone. *Journal of Risk and Insurance*, *78*, 361–388.

Laury, S., & McInnes, M. (2003). The impact of insurance prices on decision making biases: An experimental analysis. *Journal of Risk & Insurance*, *70*, 219–233.

Malmendier, U., & Tate, G. (2005). Does overconfidence affect corporate investment?: CEO overconfidence measures revisited. *The Journal of Finance*, *11*, 649–659.

Moore, D., & Healy, P. (2008). The trouble with overconfidence. *Psychological Review*, *115*, 502–517.

Pyszczynski, T., Holt, K., & Greenberg, J. (1987). Depression, self-focused attention, and expectancies for positive and negative future life events for self and others. *Journal of Personality and Social Psychology*, *52*, 994–1001.

Rothschild, M., & Stiglitz, J. (1976). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The Quarterly Journal of Economics*, *90*, 629–649.

Royal, A., & Tasoff, J. (2017). When higher productivity hurts: The interaction between overconfidence and capital. *Journal of Behavioral and Experimental Economics*, *67*, 131–142.

Sandroni, A., & Squintani, F. (2007). Overconfidence, insurance, and paternalism. *American Economic Review*, *97*, 1994–2004.

Soll, J., & Klayman, J. (2004). Overconfidence in interval estimates. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*, 299–314.

Spinnewijn, J. (2013). Insurance and perceptions: How to screen optimists and pessimists. *The Economic Journal*, *123*, 606–633.